MSc. Thesis DRAFT - Underwater vehicle localisation using Extended Kalman Filter

Author: Miroslav Radojević
Supervisor: Yvan Petillot

Ocean Systems Lab
Heriot-Watt University, Edinburgh (UK)

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Abstract

In order to accomplish various missions, autonomous underwater vehicles need to be capable of estimating their position within the environment. This is a prerequisite of a successful mission since further tasks that need to be achieved strongly rely on navigation information as a source of valuable information.

This thesis is a study on application of an algorithm that would accomplish localization of an underwater vehicle using measurements from number of sensors mounted on it. Well known Extended Kalman Filter algorithm approach was initially suggested as a solution for self-localisation using sensor fusion. The work consists of introductory investigation of the topic, theoretical background, overview of the robot localisation capabilities. Introduction summarizes possible methods and obstacles arising from the nature of the underwater environment and sensor features. Second part goes deeper into the matter explaining practical solution for navigation and the details of the implementation, issues needed to be solved. Eventually, an analysis of the results is offered. Preliminary computer simulations and, eventually, the authentic results recorded from the real missions.

Emphasis is on improving the existing navigation and finding a way to correct known deficiencies, mostly due to erroneous heading measurement. Thesis is intended to report pros and cons of a practical piece of work where a scientific concept was adopted to solve a real task.

Prediction is difficult - especially of the future. . . .

Attributed to Niels Henrik David Bohr (1885-1962)

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Chapter 1

Results

It is useful to mention that there is no exact ground truth for underwater robot localization available. GPS signal could serve as an absolute position reference, in case it is available, either directly or in form of LBL. Experimental results have been obtained for different missions. Good news, however, is that the absolute depth measurement is quite accurate and frequent, making AUV localisation a 2D task.

1.1 Simulations

Real data taken from previously recorded Nessie mission were used to simulate the algorithm "offline". It is the stage intended for testing and correcting. Besides, simulating - being able to repeat the same measurement scenario enables more insight in filtering process and benefits of fusing together the sensor data. *.bag* files (`http://www.ros.org/wiki/`) containing recorded real-time messages with sensor measurements, were used as source. Furthermore, it allows designing the code in its original C++ form that will require little modification once deployed on the vehicle in form of ROS package since *.bag* files emulate authentic messages and timestamps. One of the deficiencies of the evaluation of localisation results is the fact that there is no exact ground truth to compare the result with. Dead reckoning localisation aided with occasional LBL position updates was compared with the localisation obtained after filtering (Figures 1.1, 1.2) for the recorded straight line mission.

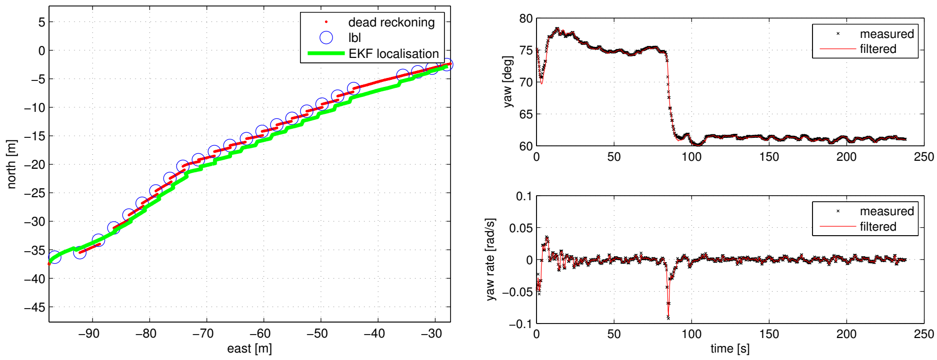
`Loch Earn dataset - straight line movement`: Example of EKF localisation using inertial measurements aided with LBL acoustic positioning system was tested on straight line movement recorded in lake Loch Earn. For simulation purposes, sensor measurements are stored in a *.bag* file, that can be replayed, producing real-time messages of sensor measurements as they originally occurred. At this point, it is important to revise which sensors were

Table 1.1: EKF navigation parameters.

Parameter	Signature [1]	Units	Description
		standard deviation of the ...	
SDNorth	σ_n	m	north observation
SDEast	σ_e	m	east observation
SDDepth	σ_d	m	depth observation
SDAltitude	σ_a	m	altitude observation
SDu	σ_u	$\frac{m}{s}$	surge velocity observation
SDv	σ_v	$\frac{m}{s}$	sway velocity observation
SDw	σ_w	$\frac{m}{s}$	heave velocity observation
SDyaw	σ_ψ	rad	heading observation
SDpitch	σ_φ	rad	pitch observation
SDyawRate	$\sigma_{\dot\psi}$	$\frac{rad}{s}$	heading rate observation
SDpitchRate	$\sigma_{\dot\varphi}$	$\frac{rad}{s}$	pitch rate observation
		standard deviation of the ... process noise	
SDuModel	$\sigma_{\dot u}$	$\frac{m}{s^2}$	surge acceleration
SDvModel	$\sigma_{\dot v}$	$\frac{m}{s^2}$	sway acceleration
SDwModel	$\sigma_{\dot w}$	$\frac{m}{s^2}$	heave acceleration
SDyawRateModel	$\sigma_{\dot v}$	$\frac{rad}{s^2}$	yaw acceleration
SDpitchRateModel	$\sigma_{\dot w}$	$\frac{rad}{s^2}$	pitch acceleration

used, their main features and, finally, filtering parameters.

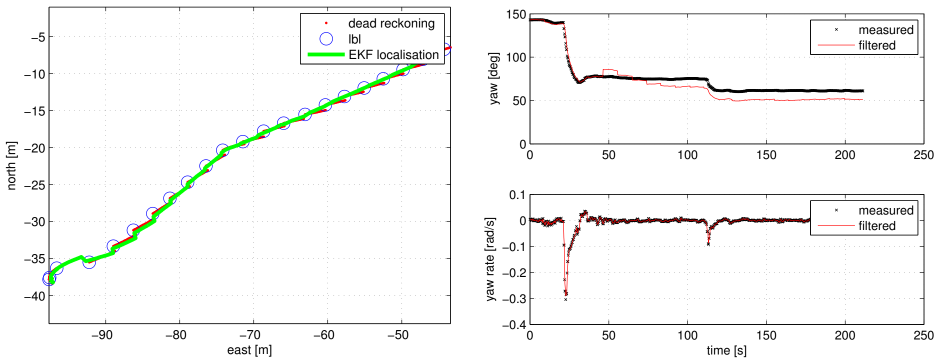
Standard sensor configuration comprising of pressure sensor, magnetic compass, FOG and DVL is used in the mission. Absolute position correction was carried out using LBL system. Important fact is that the heading was measured with compass only at the beginning. It kept being calculated by integrating yaw rate obtained from FOG, later on. Alternative solution for heading measurement is the usage of compass for direct acquiring of yaw. Result of EKF localisation algorithm was shown in north-east map (Figure 1.1(a), 1.2(a)). Different parameter values for EKF were tested. Table 1.1 revises all filter parameters used together with their role. Essentially, setting high standard deviation for a Gaussian of a certain parameter can be interpreted as having more uncertainty in value that it represents - whether it is a measurement uncertainty or uncertainty of the predicted value. Therefore, we can choose to be confident in certain sensor measurement and/or certain model prediction, and observe the simulation outcome of such setting. Setting the parameters properly tunes up the performance of a filter. Straight line movement with authentic sensor measurements recorded in Loch Earn was a basis for initial simulations of EKF localisation algorithm. Red line shows the dead reckoning navigation, which is updated with absolute position update (LBL). Dead reckoning uses values periodically ($\approx 5Hz$) obtained from DVL and FOG (linear velocities: u and v and heading ψ, respectfully), and substitutes them into equations similar to ones used for north and east



(a) N/E localisation. Yaw was calculated by integrating yaw rate measured by FOG.

(b) Heading estimation. Biased yaw measurement not being corrected.

Figure 1.1: AUV localisation using EKF with high confidence in yaw measurement, SDyaw = $0.01rad \approx 0.6°$. SDnorth/east = 5 cm, SDyawRate = 0.004 $\frac{rad}{s}$, SDu/v = $1\frac{cm}{s}$.



(a) N/E localisation. Yaw was calculated by integrating yaw rate measured by FOG.

(b) Heading estimation. Biased yaw measurement is being corrected.

Figure 1.2: AUV localisation using EKF with low confidence in yaw measurement, SDyaw = $0.2rad \approx 11.5°$. SDnorth/east = 5 cm, SDyawRate = 0.004 $\frac{rad}{s}$, SDu/v = $1\frac{cm}{s}$.

prediction within prediction model:

$$north = north + (uT + \dot{u}\frac{T^2}{2})\cos(\psi) - (vT + \dot{v}\frac{T^2}{2})\sin(\psi)$$

$$east = east + (uT + \dot{u}\frac{T^2}{2})\sin(\psi) + (vT + \dot{v}\frac{T^2}{2})\cos(\psi)$$

EKF updates periodically (synchronous mode), with period set to 230 ms. At first, simulation parameters SDnorth, SDeast, SDyaw, SDyawRate were set to low values. Generally, that suggests high trust in measurements. Result (Figure 1.1(a)) shows that the heading measurement has a constant bias, caused by the error in initial heading measurement obtained by compass. After obtaining initial heading, yaw rate was integrated in time to calculate yaw. Thus, yaw measurement, calculated relative to previous value each time, propagates the error (bias). Biased yaw observation further on causes EKF localisation to experience sharp jumps. To overcome this using EKF framework, less confidence was assigned to yaw measurement (SDyaw) when setting EKF parameter values. Eventually, bias becomes visible if measured and filtered heading are compared (Figure 1.2(b)). As for the rest of heading information, rate of yaw information will be incorporated when using EKF, this time with a lot of confidence (SDyawRate range of degrees) since it does not depend on initial estimate. Good feature of sensor fusion is that lack of one measurement or its low performance can be compensated with some other measurement considering that they are combined together in mathematical model in the right manner. In case of yaw and yaw rate - the derivation in time is a relation that connects them together.

Simulation shows that localisation performance can be tailored by setting the confidence in prediction model or measurement values. Confidence is manifested as standard deviation (variance) of the random variable: the lower it is, more certain the value of the random variable is hence more confident in value of that variable we tend to be. Kalman filter tries to optimise the result within the defined boundaries of uncertainty.

1.2 Without GPS help

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